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Dated: February 12, 2007 Signature: (Peter J. Yim)

Docket No.: 509982005500
(PATENT)

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re Patent Application of:
Srinivas DODDI et al.

Application No.: 10/608,300

Filed: June 27, 2003 Art Unit: 2121

For: OPTICAL METROLOGY OF STRUCTURES FORMED ON SEMICONDUCTOR WAFERS USING MACHINE LEARNING SYSTEMS

Examiner: N. Brown

APPEAL BRIEF

MS APPEAL BRIEF
Commissioner for Patents
P.O. Box 1450
Alexandria, Virginia 22313-1450

Dear Sir:

This brief is in furtherance of the Notice of Appeal, filed in this case on December 11, 2006. The fees required under § 1.17(f) and any required petition for extension of time for filing this brief and fees therefore, are dealt with in the accompanying TRANSMITTAL OF APPEAL BRIEF.

This brief contains items under the following headings as required by 37 C.F.R. § 41.37 and M.P.E.P. § 1205:

I. Real Party in Interest
II. Related Appeals and Interferences
III. Status of Claims
IV. Status of Amendments
V. Summary of Claimed Subject Matter
VI. Grounds of Rejection to be Reviewed on Appeal

sf-2267922

VII. Arguments
VIII. Claims Appendix
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Appendix A. Claims

I. REAL PARTY IN INTEREST

The real party in interest for this appeal is:

Timbre Technologies, Inc. of Santa Clara, California, which is a subsidiary of Tokyo Electron Limited of Tokyo, Japan.

II. RELATED APPEALS, INTERFERENCES, AND JUDICIAL PROCEEDINGS

There are no other appeals, interferences, or judicial proceedings that will directly affect or be directly affected by or have a bearing on the Board's decision in this appeal.

III. STATUS OF CLAIMS

A. Total Number of Claims in Application

There are 29 claims pending in the application.

B. Current Status of Claims

1. Claims canceled: 0
2. Claims withdrawn from consideration but not canceled: 0
3. Claims pending: 1-29
4. Claims allowed: 0
5. Claims rejected: 1-29
6. Claims objected to: 0

C. Claims on Appeal

The claims on appeal are claims 1-29.

IV. STATUS OF AMENDMENTS

No Amendments remain outstanding.

V. SUMMARY OF CLAIMED SUBJECT MATTER

Claim 1 recites a method of examining a structure formed on a semiconductor wafer. (Page 13, paragraph 54, lines 1-2; FIG. 6, 600.) A first diffraction signal measured using a metrology device is obtained. (Page 13, paragraph 54, lines 2-4; FIG. 6, 602.) A second diffraction signal generated using a machine learning system is obtained. (Page 13, paragraph 54, lines 4-5; FIG. 6, 604.) The machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system. (Page 13, paragraph 55, lines 1-3.) The first and second diffraction signals are compared. (Page 13, paragraph 54, line 5; FIG. 6, 606.) When the first and second diffraction signals match within a matching criterion, a feature of the structure is determined based on the one or more parameters of the profile used by the machine learning system to generate the second diffraction signal. (Page 13, paragraph 54, lines 5-6; paragraph 55, lines 4-6; FIG. 6, 608.)

Claim 16 recites a computer-readable storage medium containing computer executable instructions for causing a computer to examine a structure formed on a semiconductor wafer. (Page 13, paragraph 54, lines 1-2; FIG. 6, 600.) The instructions include obtaining a first diffraction signal measured using a metrology device. (Page 13, paragraph 54, lines 2-4; FIG. 6, 602.) The instructions also include obtaining a second diffraction signal generated using a machine learning system. (Page 13, paragraph 54, lines 4-5; FIG. 6, 604.) The machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system. (Page 13, paragraph 55, lines 1-3.) The instructions also include comparing the first and second diffraction signals. (Page 13, paragraph 54, line 5; FIG. 6, 606.) When the first and second diffraction signals match within a matching criterion, a feature of the structure is determined based on the one or more parameters of the profile used by the machine learning system to generate the second diffraction signal. (Page 13, paragraph 54, lines 5-6; paragraph 55, lines 4-6; FIG. 6, 608.)

Claim 22 recites a system to examine a structure formed on a semiconductor wafer. (Page 13, paragraph 54, lines 1-2; page 14, paragraph 57, lines 1-2; page 15, paragraph 60, lines 1-2; FIG.

6, 600; FIG. 8, 800; FIG. 10, 1000.) A metrology device is configured to measure a first diffraction signal from the structure. (Page 13, paragraph 54, lines 2-4; page 14, paragraph 57, lines 3-6; page 15, paragraph 60, lines 2-4; FIG. 6, 602; FIG. 8, 802; FIG. 10, 802.) A machine learning system is configured to generate a second diffraction signal. (Page 13, paragraph 54, lines 4-5; page 14, paragraph 57, lines 2-3; page 15, paragraph 60, lines 4-5; FIG. 6, 604; FIG. 8, 118; FIG. 10, 118.) The machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system. (Page 13, paragraph 55, lines 1-3.) A processor is configured to compare the first and second diffraction signals. (Page 13, paragraph 54, line 5; page 14, paragraph 57, lines 3-5; page 15, paragraph 60, lines 5-6; FIG. 6, 606; FIG. 8, 114; FIG. 10, 1002.) When the first and second diffraction signals match within a matching criterion, a feature of the structure is determined based on the one or more parameters or the profile used by the machine learning system to generate the second diffraction signal. (Page 13, paragraph 54, lines 5-6; paragraph 55, lines 4-6; page 14, paragraph 56, lines 8-10; page 15, paragraph 60, lines 6-12; FIG. 6, 608.)

VI. GROUNDS OF REJECTION TO BE REVIEWED ON APPEAL

A. Whether claims 1-6, 11-14, and 16-19 are patentable under 35 U.S.C. § 103(a) over U.S. Patent No. 6,650,422 (the Singh reference) in view of U.S. Patent No. 6,192,103 (the Wormington reference).

B. Whether claims 9-10 and 15 are patentable under 35 U.S.C. § 103(a) over the Singh reference in view of the Wormington reference and further in view U.S. Patent No. 6,665,446 (the Kato reference).

C. Whether claim 7 is patentable under 35 U.S.C. § 103(a) over the Singh reference in view of the Wormington reference and further in view of EP Patent No. 0 448 890 (the Sirat et al. reference).

D. Whether claim 8 is patentable under 35 U.S.C. § 103(a) over the Singh reference in view of the Wormington reference and further in view of Gahegan et al "Dataspaces as an organizational concept for the neural classification of geographic datasets", 1999.

VII. ARGUMENT

Pending claims 1-29 have been rejected under 35 U.S.C. 103. Applicants respectfully request reversal of the Examiner's rejection of claims 1-29 in view of the following remarks.

A. **Claims 1-6, 11-14, and 16-29**

The Examiner rejected Claims 1-6, 11-14, and 16-29 under 35 U.S.C. 103(a) as being unpatentable over U.S. Patent No. 6,650,422 (the Singh reference) in view of U.S. Patent No. 6,192,103 (the Wormington reference).

Independent claims 1, 16, and 22 recite that the second simulated diffraction signal is generated **as an output of the machine learning system**. Note, claims 1, 16, and 22 do not merely recite that the second simulated diffraction signal is generated as an output, or that the machine learning system is used in generating the second simulated diffraction signal. Instead, claims 1, 16, and 22 expressly recite that the output of the machine learning system is the second simulated diffraction signal. Applicants assert that the Examiner is making a clear error by failing to establish where this claim element is disclosed in the Wormington reference.

1. **New Parameter Vector is Output of Genetic and Evolutionary Algorithms in Wormington Reference**

The Examiner has asserted that the X-ray scattering disclosed in the Wormington reference corresponds to the second simulated diffraction signal recited in claims 1, 16, and 22. Additionally, the Examiner has asserted that the genetic and evolutionary algorithms disclosed in the Wormington reference correspond to the machine learning system recited in claims 1, 16, and 22.

Thus, to be logically consistent, the Examiner must establish that the X-ray scattering disclosed in the Wormington reference is generated **as an output of the genetic and evolutionary algorithms**. It is not sufficient to simply establish that X-ray scattering is produced as an output because claims 1, 16, and 22 explicitly recite that the second simulated diffraction signal (which the Examiner has asserted corresponds to the X-ray scattering) is an **output of the machine learning system** (which the Examiner has asserted corresponds to the genetic and evolutionary algorithms).

The Wormington reference discloses using a genetic algorithm, particularly an evolutionary algorithm, **to form a new parameter vector** from two parameter vectors (see e.g. col. 3, lines 48-52) and **not a diffraction signal**. Thus, the output of the genetic algorithm is a new parameter vector rather than the X-ray scattering.

In the final Office Action, the Examiner states that, "Applicant's argument that Wormington et al. don't generate a simulation of X-ray scattering as output at 40 ignores the fact that step 40, as depicted in Fig. 4, is not an output step." Applicants believe that the Examiner has misunderstood the Applicants' argument.

Applicants' argument with regard to the output of step 40 in FIG. 4 was to establish that the Wormington reference discloses that the output of the genetic algorithm is a new parameter vector rather than an X-ray scattering. Whether or not the output of step 40 is the ultimate output of the process depicted in FIG. 4 is not relevant to the issue at hand (i.e., determining what is the output of the genetic algorithm disclosed in the Wormington reference).

Clearly when a step of a process is performed, there is an output of that step, even if that output is not the ultimate output of the process. In particular, step 40 is to "ADJUST MODEL PARAMETERS." Thus, adjusted model parameters are the output of having performed step 40. Similarly, step 34 is to "COMPUTE SIMULATION." Thus, a computed simulation is the output of having performed step 34. Because step 34 is performed before step 40, the computed simulation exists before the adjusted model parameters.

Column 6, lines 14-16 clearly disclose that the computed simulation generated as an output of step 34 is the X-ray scattering. Column 8, lines 3-7, discloses, "the adjustment of the model parameters at step 40, to obtain the best fit, is carried out with the use of genetic algorithms." Thus, the X-ray scattering (corresponding to step 34) exists before the genetic algorithm is used to adjust the model parameters (corresponding to step 40). Thus, X-ray scattering (which the Examiner has asserted corresponds to the second diffraction signal) can not be the output of the genetic algorithm (which the Examiner has asserted corresponds to the machine learning system).

2. Singh Reference Fails to Disclose Diffraction Signal Generated Using Machine Learning System

With respect to the Singh reference, the Examiner states that the Singh reference fails to disclose obtaining a second diffraction signal using a machine learning system, wherein the machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal, recited in independent claims 1, 16 and 22.

Therefore, Applicants assert that claims 1, 16, and 22 are allowable because neither the Singh nor the Wormington reference, individually or in combination, teach or suggest using a machine learning system to generate a simulated diffraction signal **as an output of the machine learning system**. Additionally, Applicants assert that claims 2-6, 11-14, 17-21, and 23-29 are allowable for at least the reason that they depend on an allowable independent base claim.

B. Claims 9-10 and 15

The Examiner rejected claims 9-10, and 15 under 35 U.S.C. 103(a) as being unpatentable over the Singh reference in view of the Wormington reference and further in view of US Patent No. 6,665,446 (the Kato reference).

The rejection of claims 9-10 and 15 should be reversed for at least the reason that they depend on an allowable independent base claim.

C. Claim 7

The Examiner rejected claim 7 under 35 U.S.C. 103(a) as being unpatentable over the Singh reference in view of the Wormington reference and further in view of EP Patent No. 0 448 890 (the Sirat et al. reference).

The rejection of claim 7 should be reversed for at least the reason that it depends on an allowable independent base claim.

D. Claim 8

The Examiner rejected claim 8 under 35 U.S.C. 103(a) as being unpatentable over the Singh reference in view of the Wormington reference and further in view of Gahegan et al "Dataspaces as an organizational concept for the neural classification of geographic datasets", 1999.

The rejection of claim 8 should be reversed for at least the reason that it depends on an allowable independent base claim.

E. Conclusion

For the forgoing reasons, Applicant requests reversal of the Examiner's rejections of claims 1-29.

VIII. CLAIMS APPENDIX

A list of the claims involved in the present appeal is attached hereto as Appendix A.

IX. EVIDENCE APPENDIX

None.

X. RELATED PROCEEDINGS APPENDIX

None.

In the event the U.S. Patent and Trademark office determines that an extension and/or other relief is required, Applicants petition for any required relief including extensions of time and authorizes the Commissioner to charge the cost of such petitions and/or other fees due in connection with the filing of this document to Deposit Account No. 03-1952 referencing docket no. 509982005500. However, the Commissioner is not authorized to charge the cost of the issue fee to the Deposit Account.

Dated: February 12, 2007

Respectfully submitted,

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sf-2267922

APPENDIX A

Claim 1: A method of examining a structure formed on a semiconductor wafer, the method comprising:

obtaining a first diffraction signal measured using a metrology device;

obtaining a second diffraction signal generated using a machine learning system,

wherein the machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system;

comparing the first and second diffraction signals; and

when the first and second diffraction signals match within a matching criterion, determining a feature of the structure based on the one or more parameters of the profile used by the machine learning system to generate the second diffraction signal.

Claim 2: The method of claim 1, further comprising:

prior to generating the second diffraction signal, training the machine learning system using a set of training input data and a set of training output data,

wherein each of the training input data is a profile of the structure characterized by one or more parameters, and

wherein each of the training output data is a diffraction signal corresponding to the profile of the structure.

Claim 3: The method of claim 2, further comprising:

selecting the set of training input data from a range of profiles of the structure.

Claim 4: The method of claim 3, further comprising:

dividing the range of profiles into a first partition and at least a second partition,

wherein a first machine learning system is configured and trained for the first partition, and a second machine learning system is configured and trained for the second partition.

Claim 5: The method of claim 2, wherein the set of training output data is generated based on the set of training input data using a modeling technique prior to training the machine learning system.

Claim 6: The method of claim 5, wherein the modeling technique includes rigorous coupled wave analysis, integral method, Fresnel method, finite analysis, or modal analysis.

Claim 7: The method of claim 2, wherein the training output data includes a plurality of dimensions, and further comprising:

transforming the training output data using principal component analysis.

Claim 8: The method of claim 7, further comprising:

dividing the dimensions of the training output data into a first partition and at least a second partition,

wherein a first machine learning system is configured and trained for the first partition, and a second machine learning system is configured and trained for the second partition.

Claim 9: The method of claim 2, wherein training comprises:

(a) obtaining a training input data;

(b) generating a diffraction signal with the machine learning system using the training input data;

(c) comparing the diffraction signal with the training output data corresponding to the training input data used to generate the diffraction signal;

(d) when the diffraction signal and the training output data do not match within a matching criterion, repeating (b) and (c) with another training input data.

Claim 10: The method of claim 2, wherein training comprises using a back-propagation, radial basis network, support vector, or kernel regression algorithm.

Claim 11: The method of claim 1, wherein when the first and second diffraction signals do not match within the matching criterion, comparing the first diffraction signal with another diffraction signal from a library of diffraction signals, and wherein the diffraction signals in the library of diffraction signals were generated using the machine learning system.

Claim 12: The method of claim 1, wherein when the first and second diffraction signals do not match within the matching criterion, generating another diffraction signal using the machine learning system to compare to the first diffraction signal.

Claim 13: The method of claim 1, wherein the metrology device is an ellipsometer, reflectometer, atomic force microscope, or scanning electron microscope.

Claim 14: The method of claim 1, wherein the one or more parameters includes one or more of critical dimension measurements, angle of incidence, n and k values, or pitch.

Claim 15: The method of claim 1, wherein the machine learning system is a neural network.

Claim 16: A computer-readable storage medium containing computer executable instructions for causing a computer to examine a structure formed on a semiconductor wafer, comprising instructions for:

obtaining a first diffraction signal measured using a metrology device;

obtaining a second diffraction signal generated using a machine learning system,

wherein the machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system;

comparing the first and second diffraction signals; and

when the first and second diffraction signals match within a matching criterion, determining a feature of the structure based on the one or more parameters of the profile used by the machine learning system to generate the second diffraction signal.

Claim 17: The computer-readable storage medium of claim 16, further comprising instructions for:

prior to generating the second diffraction signal, training the machine learning system using a set of training input data and a set of training output data,

wherein each of the training input data is a profile of the structure characterized by one or more parameters, and

wherein each of the training output data is a diffraction signal corresponding to the profile of the structure.

Claim 18: The computer-readable storage medium of claim 17, wherein the set of training output data is generated based on the set of training input data using a modeling technique prior to training the machine learning system.

Claim 19: The computer-readable storage medium of claim 17, wherein training comprises:

(a) obtaining a training input data;

(b) generating a diffraction signal with the machine learning system using the training input data;

(c) comparing the diffraction signal with the training output data corresponding to the training input data used to generate the diffraction signal;

(d) when the diffraction signal and the training output data do not match within a matching criterion, repeating (b) and (c) with another training input data.

Claim 20: The computer-readable storage medium of claim 16, wherein when the first and second diffraction signals do not match within the matching criterion, comparing the first diffraction signal with another diffraction signal from a library of diffraction signals, and wherein the diffraction signals in the library of diffraction signals were generated using the machine learning system.

Claim 21: The computer-readable storage medium of claim 16, wherein when the first and second diffraction signals do not match within the matching criterion, generating another diffraction signal using the machine learning system to compare to the first diffraction signal.

Claim 22: A system to examine a structure formed on a semiconductor wafer, the system comprising:

a metrology device configured to measure a first diffraction signal from the structure;

a machine learning system configured to generate a second diffraction signal,

wherein the machine learning system receives as an input one or more parameters that characterize a profile of the structure to generate the second diffraction signal as an output of the machine learning system; and

a processor configured to compare the first and second diffraction signals,

wherein when the first and second diffraction signals match within a matching criterion, a feature of the structure is determined based on the one or more parameters or the profile used by the machine learning system to generate the second diffraction signal.

Claim 23: The system of claim 22, wherein prior to generating the second diffraction signal, the machine learning system is trained using a set of training input data and a set of training output data,

wherein each of the training input data is a profile of the structure characterized by one or more parameters, and

wherein each of the training output data is a diffraction signal corresponding to the profile of the structure.

Claim 24: The system of claim 23, wherein the set of training input data is selected from a range of profiles of the structure.

Claim 25: The system of claim 24, wherein the range of profiles is divided into a first partition and at least a second partition, and the machine learning system comprises:

a first machine learning system configured and trained for the first partition; and

a second machine learning system configured and trained for the second partition.

Claim 26: The system of claim 23, wherein the training output data includes a plurality of dimensions, and the dimensions of the training output data is divided into a first partition and at least a second partition, and wherein the machine learning system comprises:

a first machine learning system configured and trained for the first partition; and

a second machine learning system configured and trained for the second partition.

Claim 27: The system of claim 22, further comprising:

a library of diffraction signals, wherein the diffraction signals in the library were generated using the machine learning system,

wherein when the first and second diffraction signals do not match within the matching criterion, the first diffraction signal is compared with another diffraction signal from the library of diffraction signals.

Claim 28: The system of claim 22, wherein when the first and second diffraction signals do not match within the matching criterion, the machine learning system generates another diffraction signal to compare to the first diffraction signal.

Claim 29: The system of claim 22, further comprising:

a semiconductor fabrication unit coupled to the processor, the semiconductor fabrication unit configured to perform one or more fabrication steps.